Semantic Segmentation Based Earthquake Damage Assessment of Built Environment

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Abstract

This research focuses upon determining the feasibility of using image-based deep learning techniques for inspecting the damage detection and its category in the building components after the earthquake. It will help in deciding whether the building is safe to occupy or not after the occurrence of the earthquake. Residential building images from the 2015 Nepal earthquake, the Haiti earthquake in 2010, the Taiwan earthquake in 2016, and Ecuador earthquake in 2016 are used for damage prediction in different components of a building. In this study, a deep learning model is used for determining the earthquake damage prediction. The model uses the semantic-segmentation technique for segmenting the of building's images into three categories, structural components (i.e., columns), non-structural components (i.e., walls) and all other components including doors, windows, ceilings into background category. After the segmentation of the components, it aims to detect the damage type in the identified components simultaneously. For fine-tuning the model, 85% of the total datasets were used for training, and 15% of them were used for validation. Our model achieved a validation accuracy of 86.75% and a training accuracy of 88.44%.

1 Introduction

As earthquakes occur in certain places, it ultimately affects the sustainability of the structures. Thus, impacting the health and life of the people who are still living in those buildings. This may cause many problems in the long run as there are many major and minor damages which the buildings have suffered after the earthquake. There is a high probability of these damages getting undetected, which may lead to compromise with integrity and strength of the structure. Loss in the strength of the buildings makes it unsafe to occupy after the disaster, and as such, there is no guarantee that building will be in its a functional state. Thus, a post-disaster assessment is therefore essential for assessing the full disaster's impact and defining the needs for recovery of the components of the building. This assessment will try to act as an aid for designing and implementing the strategies for the recovery of the components of the buildings and may be able to guide the funding which the donor has provided wisely. This assessment also tries to look upon restoring the damaged infrastructures, services, livelihoods, governance, nearby houses, and social systems. It also tries to reduce the future risks from the disasters and thus helping in building resilience. One of the best ways is to carry out a detailed structural inspection of the buildings and all it is components, to carry out the damage level inspection and make predictions about the building functionality. However, the significant problem which arises with the detailed structural inspection is that it takes much time to analyze and make predictions for each of the components and determining the current state of occupancy for the building. Another, the issue is that it is too costly to conduct the structural inspection, as it requires a lot of labor, equipment, and other resources. Apart from time and money, it also depends upon many other factors and synchronization of the team collectively for conducting the inspection, which makes it even more difficult. Thus, a detailed inspection will, therefore, be unable to alert the people who are still occupying the building, and it will be challenging to comment upon building functionality in a short period, as many lives will be in danger if the people still occupy the building which is not currently safe to occupy. Thus, to overcome this problem and give an alert to the people who are staying in the buildings within a short period of time about the building functionality and its current status, we have focused upon building a image-based deep learning visual inspection method using the techniques of semantic segmentation for prediction and detection of damage levels which the buildings have suffered after the earthquake.

Semantic segmentation models have capabilities of capturing the context, enabling precise localization and providing detailed segmentations (Girshick et al. 2014; Long, Shelhamer, and Darrell 2015; Ronneberger, Fischer, and Brox 2015). Hong et al. 2018 have worked to address the gap migrating segmentation model trained in a virtual environment to the real world.

Researchers have worked on damage detection by inspecting UAV images using Faster Region-based Convolutional

Neural Network (Faster R-CNN) method (Cha et al. 2018; Kang and Cha 2018; Lin, Nie, and Ma 2017). Damage recognition and classification have been performed on the still images using neural network architectures such as VGG16, AlexNet, and GoogleNet (Gao and Mosalam 2018; Wang et al. 2018). Yang et al. 2018 applied semantic segmentation fully convolution Network (FCN) network for pixel-level crack identification and measurement.

Although the visual inspection method is not as accurate as detailed inspection, but this method has two advantages over the manual inspection method, i.e., it is an efficient method in terms of both time and cost. Moreover, since, it is efficient in time so it will be an easy task using the visual inspection for determining the building functionality and would save many lives from the danger. Thus, we are making a tradeoff between accuracy and time to prevent people from occupying the buildings just after the occurrence of an earthquake.

2 Methodology

For the damage level prediction and inspection of the damages in buildings, we have built an image-based deep learning model, using techniques of semantic segmentation for this purpose. We have considered only those images which consist of the internal components of the buildings. The research focused upon classifying the building's structural components (i.e., columns), non-structural components (i.e., walls) and classifying the background, furniture, doors, windows, fall ceilings into other categories and finally detecting the reason of damage in that identified component.
Our model focuses upon segmenting the images into three categories namely the columns (structural component), walls (non-structural components) and all other internal components present in the building except the columns and walls into the background category. Moreover, our model simultaneously aims to predict the reason for the damage in the identified components (i.e., either walls or columns) using the techniques of the semantic segmentation.

The pixel values assigned to each of the seven categories is listed in Table 1. We have used a dataset of approximately 449 images for training our first segmentation model. Out of 449 images, 380 were used for training, and 69 images were used for validation.

Categories for Classification	Pixel values (RGB)		
	Red	Green	Blue
diagonal crack in wall	255	0	0
Horizontal crack in the wall	112	48	160
No crack in the wall	143	170	220
Column crushing	56	87	35
Column buckling	127	96	0
No damage in column	132	60	12
Background	29	154	120

Table 1: Pixel (RGB) values for each of the seven categories

3 Architecture

Our model followed the U-net [Ronneberger, Fischer, and Brox 2015] architecture for performing the semantic segmentation into seven different categories. Both the models were made of an encoder-decoder network where the feature maps from each encoder layers were stored and directly transferred to corresponding layers in the decoder network for the concatenation. All feature maps were transferred instead of taking the indices to get higher accuracy. The encoder network consisted of Convolution layers along with batch normalization layers, ReLU non-linear activation layers, and max-pooling layers. The decoder network consisted of UpSampling layers performed by Conv2DTranspose layers, Convolution layers along with batch-normalization layers and SpatialDropout2D layers with a dropout value of 0.5. No Max-Pooling layers were present in the decoder network. Finally, a softmax activation layer was present at the end of both the models which gave the probabilistic score of each of the class. Binary-Cross Entropy loss function was used along with Adam's Optimizer with a starting learning rate of 0.0001 for minimizing the loss function. The model was fine-tuned for 60 epochs. The batch size of the training datasets was eight whereas, for validation datasets, the batch-size value was kept as 1. Thus, each epoch consisted of 48 iterations of both feed-forward and backward propagations simultaneously. Four Callbacks functions were used for training our model. One callback class was defined to calculate the mIoU metric and for checking how the network is learning. Moreover, other than user-defined callback function, we also used inbuilt callbacks in Keras library, i.e., ReduceLROnPlateau, ModelCheckpoint, and CSVLogger functions.

4 Classification of Categories

Our model tries to classify every pixel of the image into seven different categories based upon the component identification and the type of the damage which that component has suffered. These seven different categories are:

- Diagonal crack in a wall: Diagonal cracks indicate a mode of failure in the wall when tensile stresses developed in the wall exceeds the tensile strength of the wall.
- Horizontal cracking wall: This occurs because of unbalanced soil pressure. As during an earthquake, a structure is subjected to uneven forces from below the ground this results in unbalanced pressure on soil, which in turn cause cracks.
- No cracks in wall: This classification is for the walls which do not have any crack. These walls are safe and do not cause any danger to the overall structure.
- Crushing of column: This is a standard failure mode in the column; in this mode, the load on concrete exceeds the load for which it was designed. As a result, column crushes due to excess load and may lead to failure of the entire structure.

- Buckling of the column: In this failure mode, the bending moment on the column exceeds designing value of bending moment and thus the column buckles. Buckling occurs suddenly and results in large deflections perpendicular to the length of the column.
- No damage in the column: This is a simple classification for columns that are not damaged and hence safe.
- Background: This classification is for components other than column and wall in a structure. This includes all the other possible objects or component of structure like doors, windows, and furniture.

5 Database Generation

For doing this research work, earthwork renaissance building images were collected from various open sources which are available to the public at Datacenterhub.com and eqclearinghouse.org [EERI]. This includes buildings images from the Pohang Earthquake in 2017 [Chungwook et al. 2018], Nepal earthquake in 2015 [Prateek et al. 2015], Ecuador earthquake in 2016 [Chungwook et al. 2016], and the Taiwan earthquake in 2016 [NCREE 2016]. A total of approximately 449 interior images of the buildings were used for damage level detection and inspection of the building components by the semantic segmentation model. Our aim was to predict the damage type in the components, i.e., in walls and columns. So, we labelled each image, such that in each image the component is detected, as well as the type of damage which the component has suffered because of the earthquake. Thus, we have labelled the columns and walls in each image if present, based on the damage which it has suffered. The columns in an image were labelled into 3 categories. Column crushing class indicates that the column has been damaged due to crushing, Column buckling indicates that the column has been damaged due to buckling and No damage in the column indicates that the column is safe. Similarly, walls if present in any image were labelled into 3 categories. Diagonal cracks in the wall indicate that tensile stresses have dominated in walls, Horizontal cracks in walls indicates that the damage is due to an imbalance in the soil pressure and No cracks in the wall indicates that the walls are safe. Other than walls and columns, all things which were present in the images were labelled to background class. Columns, walls, and background were labelled simultaneously in every image. Each model was trained using 380 images and validated using 69 images.

6 Results

Our model achieved a validation accuracy of around 86.75% and a training accuracy of around 88.44%. The mean intersection over union (mIOU) value was calculated over all the datasets which we used for validation. The mIOU value our model got on validation dataset was 0.74909. Training and Validation Accuracies are shown in Fig 1. Images, along with their original masks and predicted masks are shown in Fig 2 below.

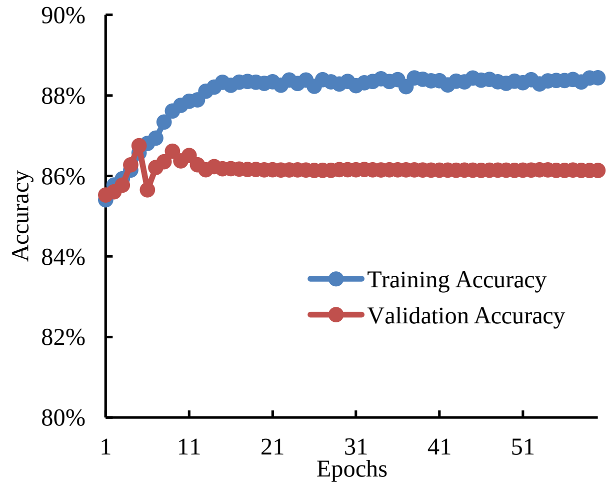

Fig 1: Training and Validation Accuracies vs. Epochs

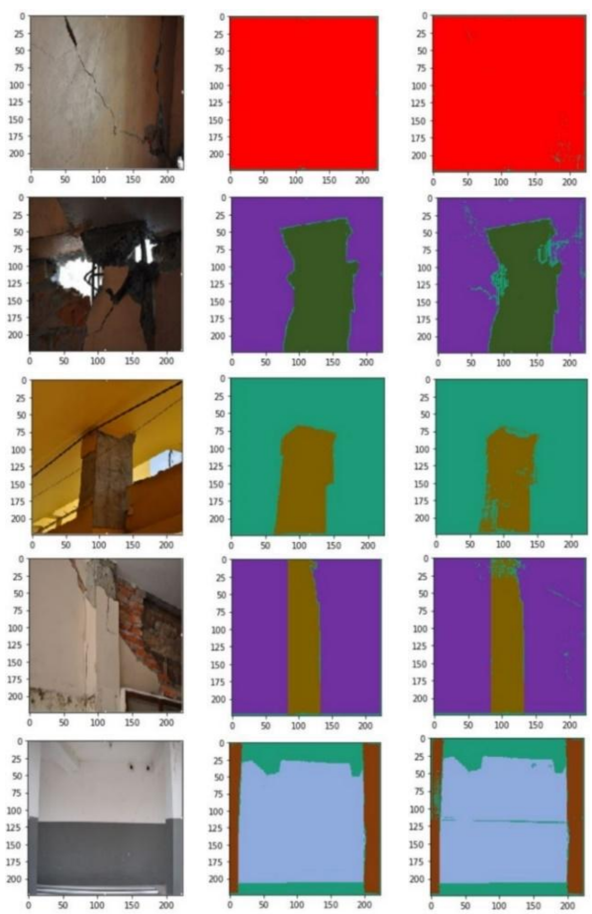

Fig 2: Images represented with their original masks and predicted masks by our model representing all seven different categories

7 Conclusion

An image-based deep learning model was defined for predicting, if the component is damaged or not, and if it is then, we predicted the type of damage in that component using the techniques of semantic segmentation as described earlier. Our model focused majorly on two of the components of the buildings for detection, i.e., walls and columns.

8 Future Work

Currently, we have designed our model to identify damages only in columns and walls. In the future, we can extend this model to identify damages in other structural components like beams, footings as well. We can also identify the reason for damage in a structural component if it is due to concrete failure or steel failure just based on the image. In this way, this model can be enhanced from essential building damage detection to identifying the exact reasons for the component failure.

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